Bridging Lexical Divergence: LLM-Assisted, Cost-Efficient Zero-Shot Scientific Entity Linking

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Abstract

Scientific domain entity linking (EL) differs from general domain EL because mentions and entity names often lack lexical overlap. Another challenge is that specialized terminology is used in the scientific domain, which is rarely encountered in a model pretrained on a general domain. Therefore, models trained on general domain transfer poorly to scientific domain. To address these, in-domain fine-tuning is the natural remedy. However, many scientific domains lack expert-annotated data, motivating the need for a zero-shot approach. Existing zero-shot methods heavily rely on LLMs to generate aliases across entire mention corpora, which incurs substantial computational cost, and those methods provide no mechanism to filter out if any noise from LLM. To address these challenges, we propose Sci-ZSEL[1], a zero-shot framework that selectively generates entity aliases with LLM to control computational cost, and applies an ontology-aware filter to remove aliases that semantically drift toward ontology neighbors. Then, filtered aliases are used to construct pseudo-labeled mention-entity pairs for zero-shot fine-tuning. To enable evaluation of EL under low lexical overlap, we also release a new animal science EL benchmark linked to three livestock trait ontologies, where mentions and entities exhibit substantially lower lexical overlap than in existing benchmarks. Across five benchmarks, Sci-ZSEL outperforms the non-fine-tuned baseline, and combining Sci-ZSEL with curated synonyms achieves the best performance in most settings.

1 Introduction

Entity Linking (EL) identifies mentions in text and links them to entities in a **Knowledge Graph (KG)**. Most EL research targets **general domain EL**, where the central challenge is **disambiguation** among candidates with similar surface forms (e.g., "Apple" the company vs. the fruit). **Zero-Shot Entity Linking (ZSEL)** aims to perform linking without requiring human-annotated training data. Recent ZSEL approaches (Wu et al., 2020; Xu et al., 2023b) have made significant progress by leveraging entity descriptions and contextual embeddings to resolve such ambiguities. However, these methods are typically trained on open-domain corpora such as Wikipedia, where mentions and entities often exhibit high lexical overlap.

Scientific domain EL faces a different challenge from general domain EL, where mentions and entity names often **lack lexical overlap**. Rather than resolving ambiguity among lexically similar candidates, scientific EL must handle highly variable terminology, where formal names may differ significantly from their common or colloquial names. For example, a paper may use “lambing potential” instead of “goat fertility”, and “hypertension” instead of “high blood pressure”. This **lexical divergence** poses a major obstacle for standard approaches, which rely on token-level similarity. Another unique characteristic of scientific EL is that the KG is often represented as an ontology, with terms organized in hierarchical structures that show relationships between concepts. Such information is not sufficiently leveraged in existing ZSEL models trained on general domain corpora.

Consequently, pretrained ZSEL models struggle with scientific EL tasks. First, due to differences in lexical challenges between general and specialized scientific domains, they struggle to transfer effectively. Second, they cannot handle specialized terminology that the general domain rarely encounters. Third, pretrained ZSEL models ignore the ontology structure, treating each entity as an isolated string and missing the hierarchical signal that distinguishes closely related concepts. All limitations point to fine-tuning on in-domain data as the natural remedy, and prior work has taken this route

[1]Code and data: https://anonymous.4open.science/r/ent-linking-FB85

(Yuan et al., 2022; Xu et al., 2023a). However, fine-tuning requires labeled mention-entity pairs, and expert annotation is expensive and unavailable in many specialized domains. Recent work uses LLM to synthesize training data (Xin et al., 2025; Ye and Mitchell, 2025). Still, these methods use an LLM for each mention: the token cost scales with the size of the corpus, and the generated pairs are tied to that corpus rather than being reusable across new corpora drawn from the same ontology.

To address these challenges, we propose Sci-ZSEL, a cost-aware zero-shot framework that does not require human-labeled mention-entity pairs from the target domain. The framework generates pseudo-labeled training pairs by prompting an LLM for alias names that serve as lexical bridges between corpus mentions and ontology entities. To bound LLM cost, we apply this augmentation on the entity side rather than the mention side: instead of issuing one LLM call per corpus mention, we identify a small set of entities and generate aliases for each, then use those aliases to find mentions to form mention-entity pairs for fine-tuning. To ensure that LLM-generated aliases properly align with the entities in the ontology, we further apply an ontology-aware filter that uses entity hierarchy and semantic similarity to discard drifted aliases before training.

We further release a new EL benchmark drawn from animal science literature. This dataset is curated by domain experts and highlights the lexical divergence challenge in scientific EL tasks.

Our main contributions are as follows:

- A new animal science EL benchmark dataset formed based on PubMed articles linked to three livestock trait ontologies.
- **Sci-ZSEL**, a zero-shot EL framework that uses an LLM to generate alias names for selected entities and builds pseudo pairs from real mentions and original entity names.
- Sci-ZSEL improves over the non-fine-tuned baseline across all five benchmarks; moreover, combining Sci-ZSEL generated aliases with curated synonyms achieves the best performance in most settings.

2 Related Work

2.1 General Domain Entity Linking

General domain EL primarily targets *disambiguation* among lexically similar candidates. Early systems exploited surface overlap and context heuristics (Cucerzan, 2007; Ratinov et al., 2011), and later methods used pretrained language model and introduced dense semantic representations that improved robustness to surface variation (Yamada et al., 2016; Gillick et al., 2019), they assume substantial lexical overlap between mention and entity, which is an assumption that fails in scientific text.

2.2 Zero-Shot Entity Linking

ZSEL removes dependence on in-domain labeled mentions by linking through entity descriptions that enable generalization to unseen entities (Logeswaran et al., 2019; Wu et al., 2020; Xu et al., 2023b). Existing ZSEL methods show strong performance on Wikipedia-style benchmarks where mentions and entity names have lexical overlap, but they implicitly rely on surface-form similarity and transfer poorly to specialized domains where mentions and entities may share no lexical overlap at all.

2.3 Zero-Shot Biomedical Entity Linking

Biomedical EL faces this lexical divergence most acutely: abbreviations, acronyms, and synonyms produce mention-entity pairs with minimal surface overlap (e.g., "EGFR" vs. "Epidermal Growth Factor Receptor"). Early dictionary and rule-based methods offer high precision but limited scalability (Aronson, 2001; Leaman et al., 2013). Neural approaches with domain-specific encoders (Liu et al., 2021; Chen et al., 2021), generative formulations (Yuan et al., 2022), and cross-entity interaction (Xu et al., 2023a; Kim et al., 2025) can improve performance but still depend on large expert-annotated corpora for fine-tuning, which are unavailable in emerging scientific domains where ontology synonyms are also sparse.

2.4 LLM-Based Data Augmentation

Recent work uses LLMs to synthesize EL supervision, either by augmenting mention contexts or by acting as end-to-end disambiguators (Xin et al., 2025; Sanz-Cruzado and Lever, 2025; Ye and Mitchell, 2025). These approaches generate per mention, so token cost scales with corpus size, and no guard against drift. Sci-ZSEL inverts the direction: it generates aliases for a subset of entities, pairs them with observed corpus mentions, and applies a filter to discard drifted aliases, which combines the semantic reach of LLMs with the efficiency of a compact retriever-reranker pipeline.

3 Animal Science Benchmark

Animal science research on quantitative trait loci (QTL) requires normalizing free-text trait mentions to enable combining findings across studies. Trait names, however, differ across research aspects, species, and product lines, and are therefore curated in separate ontologies.

In the proposed animal science benchmark, the EL task utilizes three livestock trait ontologies, Clinical Measurement Ontology (CMO), Vertebrate Trait Ontology (VT), and Livestock Product Trait Ontology (LPT). Following the zero-shot setting, we do not annotate a training set. Instead, we use the QTL Benchmark released in Li et al. (2025) as the training corpus and use the CuPUL method (Li et al., 2025) to recognize trait mentions.

The test dataset is annotated manually using two strategies. First, a domain expert randomly selected 150 records from Animal QTLDB, an animal science database curated for QTL research. Each record contains a normalized trait name, the ontology IDs from the aforementioned 3 ontologies, and the corresponding publication (PubMed ID) from which the record is curated. The expert then manually identifies corresponding mentions from the full paper. Second, we obtain a comprehensive list of trait names and their synonyms from Animal QTLDB curators. Then, we collect all abstracts of papers curated in Animal QTLDB and apply string matching to identify the trait mentions. Four student annotators manually identified the entities from the three ontologies and corrected mention boundaries when needed. Finally, the domain expert validated the annotations.

The statistics of two existing biomedical benchmarks NCBI Disease (Dogan et al., 2014), BC5CDR (Li et al., 2016), and the new animal science benchmarks (CMO, VT, and LPT) are summarized in Table 1.

To characterize different levels of lexical divergence, we partition mention–entity pairs into three categories based on their degree of lexical overlap. **HO** (high overlap) refers to cases where the mention is a substring of the entity name. **LO** (low overlap) refers to cases where the mention and entity name exhibit partial lexical overlap, but the mention is not a substring of the entity name. **NO** (no overlap) refers to cases where the mention and entity name share no lexical overlap.

The resulting test sets differ from existing biomedical benchmarks in two ways. First, the NO rate is substantially higher than existing benchmarks. Moreover, the high ratio of unique mentions to unique entities indicates that the mentions are highly diverse for the same entities. On the other hand, the three ontologies from the animal science domain are less developed than those in the biomedical domains, with a lower percentage of entities with synonyms and fewer synonyms per entity. Both observations illustrate that our new animal science benchmark may be significantly harder than the existing biomedical benchmarks.

Annotation Limitations: Due to the high cost of domain-expert review, the test sets are small, which limits statistical power for fine-grained comparisons. The pipeline also carries a selection bias: we select mentions by dictionary string matching against ontology synonym lists, so mentions absent from those lists are dropped before annotators see them. For example, "IMF" is widely used for intramuscular fat in QTL articles but does not appear as a synonym in ontologies. Annotators partially offset this by manually collecting no-overlap cases, but the test mention pool remains biased toward surface forms that the ontologies anticipate.

4 Preliminaries

Let $\mathcal{E}$ be the set of entities in a target ontology and $\mathcal{M}$ the mentions extracted from an unlabeled training corpus. Each entity $e \in \mathcal{E}$ has a name $n(e)$, a definition $d(e)$, and may have a list of synonyms $\mathrm{Syn}(e)$. Given a mention $m \in \mathcal{M}$ with context $c(m)$, the task is to predict its referent entity $e \in \mathcal{E}$. For the zero-shot setting, no human-labeled $\langle m, e \rangle$ pairs are available for training.

A bi-encoder retriever maps the mention and the entity to dense vectors $\tau_m, \tau_e \in \mathbb{R}^d$ and scores them by their dot product $\tau_m \cdot \tau_e$. It returns the top-K entities under this score. We use the pretrained BLINK (Wu et al., 2020) as the bi-encoder backbone; details in Appendix A.3.

A cross-encoder reranker encodes mention m, its context $c(m)$, and all candidates e jointly to produce a score $s(m, e)$. We consider two pretrained cross-encoder backbones, BLINK (Wu et al., 2020) and ReS (Xu et al., 2023b); details in Appendix A.4.

5 Methodology

5.1 Entity Selection from the ontology

An ontology defines the vocabulary of a domain and often contains a large collection of enti-

Dataset name	Ontology Name	Test set statistics						Ontology statistics			
		Samples	HO%	LO%	NO%	Ment	Ent	Entities	Synonyms	Syn/Ent	Cov%
NCBI Disease	MEDIC	960	32.08	45.00	22.92	287	190	13,316	127,370	9.57	85.0
BC5CDR	MeSH	9465	62.07	13.77	24.16	2084	1267	355,213	757,086	2.13	94.5
CMO	CMO	2032	20.13	36.42	43.45	458	107	4,133	4,413	1.07	57.2
VT	VT	1688	8.83	34.06	57.11	500	111	4,044	3,670	0.91	44.0
LPT	LPT	722	30.75	24.24	45.01	233	103	520	462	0.89	41.7

Table 1: Combined test-set and ontology statistics. Test set block: Samples refers to the number of mention-entity pairs in the test set, HO, LO, and NO show the percentages of samples by overlap categories; and Ment and Ent refer to the number of unique mentions and unique entities in the test set, respectively. Ontology block: Entities and Synonyms refers to the total number in the ontology, Syn/Ent refers to averaged synonyms per entity, and Cov% is the percentage of entities with at least one synonym provided. Note that CMO, VT, and LPT are test-only datasets.

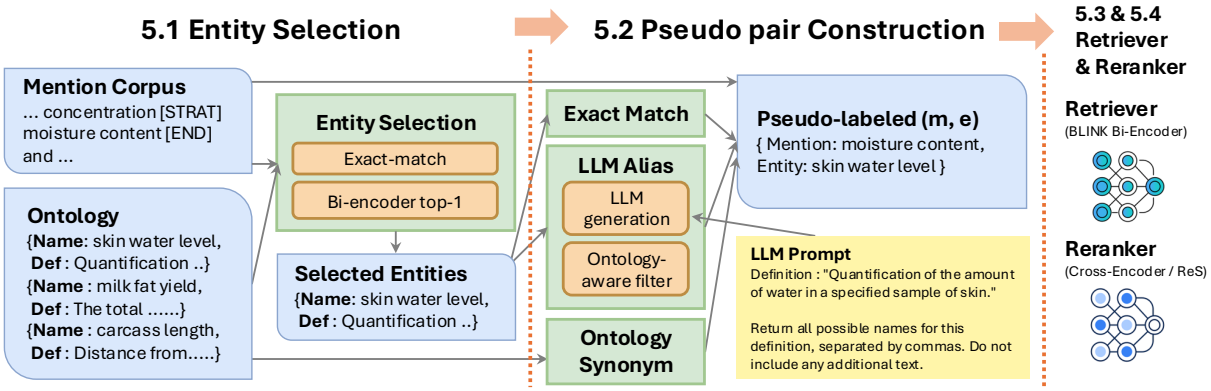

Figure 1: Sci-ZSEL pseudo pair construction with a worked example. Entities from the Ontology and Mention Corpus are fed to Entity Selection; The selected entities form pseudo-labeled pairs through three strategies: exact match, LLM-generated alias (where the entity's definition is sent to the LLM and the generated aliases are filtered), and curated ontology synonym. The resulting pseudo-labeled dataset is used to fine-tune the retriever and reranker.

ties. However, following the assumption of Zipf's law (Zipf, 1949), many of those entities are not mentioned in the target corpus, so it is unnecessary to consider every entity. Therefore, to reduce cost, Sci-ZSEL strategically selects a subset of entities and uses LLM to generate their aliases. This also makes the generated supervision reusable across corpora collected from similar domains. Figure 1 shows the entire flow of pseudo pair generation.

5.1.1 Exact match entities

In scientific domains, mention ambiguity is relatively low. If a mention matches the surface name of an entity, the pairing is usually correct. Following this assumption, we include these entities whose name appears as mentions in the corpus:

$$\mathcal{E}_{\mathrm{EM}} = \{\, e \in \mathcal{E} : \exists\, m \in \mathcal{M},\ m \equiv n(e) \,\} \quad (1)$$

5.1.2 Bi-encoder top-1 entities

A pretrained BLINK bi-encoder embeds mentions and entities into a semantic space, so top-ranked entities can provide a semantic bridge for lexically divergent mentions. To do so, we pass each mention $m \in \mathcal{M}$ to the bi-encoder and use its top-1 entity. Specifically, we define this set as $\mathcal{E}_{\mathrm{BT}}$:

$$\mathcal{E}_{\mathrm{BT}} = \{\, \mathrm{top1}_{\mathrm{BLINK}}(m) : m \in \mathcal{M} \,\} \quad (2)$$

5.2 Pseudo pair Construction

We construct pseudo-labeled pairs by using the unlabeled training corpus and the selected entities ($\mathcal{E}_{\mathrm{EM}} \cup \mathcal{E}_{\mathrm{BT}}$) from Section 5.1 via the three construction strategies below.

5.2.1 Construction from exact match

Similar to exact match entity selection, but here, we return $\langle m, e \rangle$ pair for the pseudo training data instead of entity. Mathematically, it is defined as:

$$\mathcal{P}_1 = \{\, \langle m, e \rangle : m \in \mathcal{M},\ e \in \mathcal{E},\ m \equiv n(e) \,\} \quad (3)$$

5.2.2 Construction from LLM-generated alias

LLMs possess semantic reasoning capabilities; we leverage them to generate representative aliases from entity definitions. Our goal is to synthesize valid surface forms that mentions in the corpus might use. To do so, we prompt the LLM with the definition $d(e)$ of an entity $e \in \mathcal{E}_{\mathrm{EM}} \cup \mathcal{E}_{\mathrm{BT}}$ to produce aliases $a(e)$ (the prompt template is provided in Appendix A.1). We apply alias generation to all entities in $\mathcal{E}_{\mathrm{EM}} \cup \mathcal{E}_{\mathrm{BT}}$, producing the alias set $\mathcal{E}_{\mathrm{A}}$.

Ontology-aware Filtering. A common failure mode of LLM generation is semantic drift, where an alias inadvertently describes a hierarchical neighbor of e rather than the entity itself. To mitigate this, we filter the generated aliases $a(e)$ by comparing their semantic similarity to the target entity name $n(e)$ against the entity's ontology neighbors.

We first define the ontology neighborhood of entity e using its parents, children, and siblings:

$$\mathcal{N}(e) = \text{parents}(e) \cup \text{children}(e) \quad (4)$$

$$\mathcal{N}^{+}(e) = \mathcal{N}(e) \cup \text{siblings}(e) \quad (5)$$

For each generated alias $a(e) \in \mathcal{E}_{\text{A}}$, we compute an anchor similarity to the entity name $n(e)$ and a drift similarity to its most closely related neighbor in $\mathcal{N}^{+}(e)$:

$$s_{\text{anchor}} = \text{sim}\big(n(e),\, a(e)\big) \quad (6)$$

$$s_{\text{drift}} = \max_{e_{\mathcal{N}} \in \mathcal{N}^{+}(e)} \text{sim}\big(n(e_{\mathcal{N}}),\, a(e)\big), \quad (7)$$

where $\text{sim}(\cdot,\cdot)$ denotes the cosine similarity between BioLORD (Remy et al., 2024) embeddings of two entity names. We discard alias $a(e)$ if $s_{\text{anchor}} < s_{\text{drift}}$ or $s_{\text{anchor}} < \tau$, where $\tau = 0.9$. The first condition removes aliases that are semantically closer to a neighboring entity than to the target entity e, while the second removes aliases that diverge excessively from the target entity name $n(e)$. The resulting filtered alias set is denoted as $\mathcal{E}_{\text{AF}}$.

Pseudo label Construction. Finally, we search for the filtered aliases $a(e) \in \mathcal{E}_{\text{AF}}$ within the unlabeled corpus $\mathcal{M}$. We form a pseudo-labeled pair whenever an observed mention m exactly matches a filtered alias $a(e)$ (denoted as $m \equiv a(e)$ after whitespace and case normalization). Specifically, we generate the following sets of pseudo-labeled pairs:

$$\mathcal{P}_2 = \{\langle m, e\rangle : e \in \mathcal{E}_{\text{AF}}, m \in \mathcal{M}, m \equiv a(e)\} \quad (8)$$

The combined set is:

$$\mathcal{P}_{\text{Gen}} = \mathcal{P}_1 \cup \mathcal{P}_2 \quad (9)$$

5.2.3 Construction from ontology synonym

Many ontologies contain expert-curated synonym lists designed to capture alternative surface forms of an entity's name. Therefore, we can directly leverage these curated synonyms, denoted as $s \in \text{Syn}(e)$, as highly reliable lexical bridges. We construct a pseudo-labeled pair for an entity e whenever one of its curated synonyms s exactly matches an observed mention m in the unlabeled corpus. Formally, it is defined as:

$$\mathcal{P}_{\text{Syn}} = \{\, \langle m, e\rangle : e \in \mathcal{E},\ \ m \in \mathcal{M},\ m \equiv s \,\} \quad (10)$$

5.3 Ontology-Aware retriever fine-tuning

The retriever determines which candidate entities are exposed to the reranker. We therefore fine-tune the retriever to better rank semantically related ontology entities. Hierarchical neighbors in an ontology often have related meanings; they provide informative training signals for improving retrieval under the ontology structure. To do that, we incorporate ontology-aware sampling strategies to the retriever. The **BASE** strategy treats every non-gold entity as a negative. The **RM-PCS** removes neighbors $\mathcal{N}^{+}(e)$ from the negatives. The **PC-POS** promotes parents and children $\mathcal{N}(e)$ of e, as they are added as positives, while siblings remain as negatives.

Each strategy uses an in-batch cross-entropy objective with these introduced positive and negative sets; the goal is to score positive pairs higher than negative pairs within each batch. Full formulation is in Appendix A.3.2.

5.4 Reranker fine-tuning

The primary responsibility of the reranker is to learn the accurate distinctions among relevant top-K candidates, then assign the highest score to the most accurate candidate. Therefore, ontology-aware sampling strategies do not work here. Instead, we fine-tune the BLINK cross-encoder and ReS using their standard architecture (Section 4).

For each pseudo pair $\langle m, e\rangle$, we retrieve the top-K candidates from the bi-encoder, treat e as the positive and the rest as negatives, and optimize a cross-entropy loss over the candidate set. The goal is to rank the pseudo-labeled entity at the top. Full formulation and the candidate-set augmentation rule (when e is missing from top-K) are in Appendix A.4.

6 Experimental Studies

6.1 Datasets

We evaluate Sci-ZSEL on five benchmarks. NCBI Disease (Dogan et al., 2014) (linking to MEDIC (Davis et al., 2012)) and BC5CDR (Li et al., 2016) (linking to MeSH (Lipscomb, 2000))

are existing synonym-rich biomedical benchmarks; Animal Science (CMO), Animal Science (VT), and Animal Science (LPT) are synonym-sparse animal science benchmarks released with this paper (Section 3). Training pairs are constructed as described in Section 5.2. Statistics for test sets and training pairs are in Table 1 and Table 6, respectively.

6.2 Baselines

We instantiate Sci-ZSEL on two pretrained general-domain ZSEL backbones: BLINK (Wu et al., 2020) for the retriever and reranker, and ReS (Xu et al., 2023b) for the reranker. For each backbone on each dataset, we run five fine-tuning settings to isolate the contributions. The **No fine-tune** settings uses the frozen, pretrained ZSEL backbone to exhibit the performance under scientific domain shift. **Sci-ZSEL w/o filter** fine-tunes on the unfiltered LLM-generated alias setting (omitting the step from Section 5.2.2) to see the raw impact. **Sci-ZSEL** fine-tunes after filtering, so it uses $\mathcal{P}_{\text{Gen}}$ (Eq. 9), which demonstrates the impact and necessity of the ontology-aware filter. **Synonym** uses $\mathcal{P}_{\text{Syn}}$ (Eq. 10) that exhibits whether curated synonyms alone suffice for EL, where they are abundant, and **Sci-ZSEL + Synonym** $\mathcal{P}_{\text{Gen}} \cup \mathcal{P}_{\text{Syn}}$ shows whether LLM aliases and curated synonyms are complementary.

6.3 Setups

We fine-tune two pretrained zero-shot EL backbones, BLINK and ReS, using their original architectures. In a zero-shot setting, we do not have a validation set, so best-epoch selection is not possible; we therefore fix the number of epochs and report the results from the last epoch. All reported results are means over three random seeds (0, 42, 52313). Details in Appendix A.5.

6.4 Evaluation Metrics

We evaluate the retriever using Recall@64 and the reranker using Recall@1. Recall@K measures the proportion of mentions for which the gold entity appears among the top-K candidates. We further report mean reciprocal rank (MRR), which measures the average reciprocal rank of the gold entity across test mentions, as well as results on the HO, LO, and NO subsets defined in Section 3 to assess performance under varying levels of lexical divergence.

	Exact match ($\mathcal{E}_{\text{EM}}$)			Biencoder top-1 ($\mathcal{E}_{\text{BT}}$)		
Ontology	Ent	%Syn	%Name	Ent	%Syn	%Name
MEDIC	169	26.04	54.44	636	29.87	29.09
MeSH	721	10.54	53.68	1341	8.58	41.83
CMO	58	5.17	36.21	1260	3.33	10.00
VT	20	0.00	40.00	1396	2.22	7.88
LPT	30	3.33	46.67	361	2.22	14.68

Table 2: LLM-generated alias behavior across source ontologies. Ent is the number of entities used for alias generation; %Syn and %Name are the percentages of aliases matching a curated synonym and the original entity name, respectively (the remainder are new lexical bridges).

6.5 Experimental Results

In this section, we begin by analyzing the quality of our pseudo training pairs in Section 6.5.1. Next, we evaluate the retriever's performance, presenting its overall Recall@64 scores in Table 4 and providing MRR and category-wise performance (HO, LO, and NO) in Tables 9, 10, and 11. Then, we evaluate the reranker's performance in Table 5, highlighting its overall Recall@1, MRR, and category-wise results. To ensure our findings are stable and reliable, every number we report is an average calculated across three separate test runs using random seeds 0, 42, and 52313.

Dataset	Setting	Accuracy	pseudo pair count
NCBI	P_{Gen} W/O filter	72.91	1757
	$\mathcal{P}_{\text{Gen}}$	**90.32**	1301
BC5CDR	P_{Gen} W/O filter	72.55	7447
	$\mathcal{P}_{\text{Gen}}$	**91.4**	5766

Table 3: Pseudo pair accuracy and number of generated pairs, before and after applying ontology-aware filtering on the NCBI and BC5CDR training sets.

6.5.1 Cost-efficient alias generation for lexical diversity

Cost-efficiency and reusability. Sci-ZSEL bounds LLM cost by querying aliases only for a selected subset of entities rather than every corpus mention. Comparing the ontology size (Table 1) against the selected set $\mathcal{E}_{\text{EM}} \cup \mathcal{E}_{\text{BT}}$ (Table 2), the efficiency gains are substantial for large ontologies: selected entities cover under 0.6% of MeSH and only 6.0% of MEDIC. For the smaller animal science ontologies, the percentages are unavoidably higher (31.9% for CMO, 35.0% for VT, 75.2% for LPT), a more smaller subset would yield too few pseudo-labeled pairs for effective fine-tuning; how-

Dataset	Setting	BASE	RM-PCS	PC-POS
NCBI	No fine-tune	88.12$_{\pm 0.00}$	88.12$_{\pm 0.00}$	88.12$_{\pm 0.00}$
	Sci-ZSEL w/o filter	87.74$_{\pm 0.22}$	87.01$_{\pm 1.85}$	**88.75**$_{\pm 0.36}$
	Sci-ZSEL	87.40$_{\pm 0.47}$	80.70$_{\pm 11.97}$	**87.81**$_{\pm 0.63}$
	Synonym	89.20$_{\pm 0.24}$	89.73$_{\pm 0.30}$	**90.21**$_{\pm 0.36}$
	Sci-ZSEL + Synonym	89.72$_{\pm 0.97}$	89.41$_{\pm 0.78}$	**90.80**$_{\pm 0.87}$
BC5CDR	No fine-tune	88.79$_{\pm 0.00}$	88.79$_{\pm 0.00}$	88.79$_{\pm 0.00}$
	Sci-ZSEL w/o filter	88.41$_{\pm 0.74}$	88.21$_{\pm 2.01}$	**88.93**$_{\pm 1.03}$
	Sci-ZSEL	85.27$_{\pm 1.75}$	85.41$_{\pm 0.27}$	**87.80**$_{\pm 0.74}$
	Synonym	87.22$_{\pm 0.16}$	87.13$_{\pm 0.59}$	**88.57**$_{\pm 0.50}$
	Sci-ZSEL + Synonym	87.96$_{\pm 0.48}$	86.61$_{\pm 2.16}$	**89.14**$_{\pm 0.65}$
CMO	No fine-tune	75.74$_{\pm 0.00}$	75.74$_{\pm 0.00}$	75.74$_{\pm 0.00}$
	Sci-ZSEL w/o filter	**89.96**$_{\pm 0.23}$	88.02$_{\pm 1.24}$	89.24$_{\pm 1.61}$
	Sci-ZSEL	**89.22**$_{\pm 0.86}$	88.06$_{\pm 0.25}$	88.34$_{\pm 1.37}$
	Synonym	**85.71**$_{\pm 0.40}$	85.47$_{\pm 0.49}$	85.45$_{\pm 0.91}$
	Sci-ZSEL + Synonym	88.22$_{\pm 0.89}$	89.03$_{\pm 1.68}$	**89.09**$_{\pm 1.57}$
VT	No fine-tune	72.63$_{\pm 0.00}$	72.63$_{\pm 0.00}$	72.63$_{\pm 0.00}$
	Sci-ZSEL w/o filter	**84.70**$_{\pm 0.96}$	84.52$_{\pm 1.08}$	83.69$_{\pm 0.94}$
	Sci-ZSEL	84.72$_{\pm 1.69}$	**85.51**$_{\pm 0.30}$	85.31$_{\pm 1.03}$
	Synonym	86.99$_{\pm 1.74}$	86.79$_{\pm 2.67}$	**87.91**$_{\pm 2.22}$
	Sci-ZSEL + Synonym	85.58$_{\pm 4.10}$	**88.69**$_{\pm 2.22}$	87.99$_{\pm 1.47}$
LPT	No fine-tune	68.70$_{\pm 0.00}$	68.70$_{\pm 0.00}$	68.70$_{\pm 0.00}$
	Sci-ZSEL w/o filter	70.08$_{\pm 0.28}$	70.82$_{\pm 0.97}$	**71.01**$_{\pm 0.92}$
	Sci-ZSEL	75.07$_{\pm 1.54}$	**76.87**$_{\pm 0.73}$	76.18$_{\pm 0.37}$
	Synonym	**92.43**$_{\pm 0.68}$	91.83$_{\pm 0.42}$	91.78$_{\pm 1.24}$
	Sci-ZSEL + Synonym	92.29$_{\pm 0.44}$	92.48$_{\pm 0.35}$	**92.66**$_{\pm 0.69}$

Table 4: A comparison of retriever Recall@64 across benchmarks under various negative-sampling configurations. **Bold** indicates the best results when comparing column-wise.

ever, the absolute number of processed entities remains modest (1,318, 1,416, and 391, respectively). Furthermore, since aliases are anchored to ontology entities, this supervision is reusable across any corpus linked to the same ontology, whereas per-mention augmentation is not reusable.

Alias lexical diversity. Table 2 presents LLM-generated aliases by whether they match a curated synonym (%Syn), the entity name (%Name), or neither (constituting a new lexical bridge). On synonym-sparse animal science ontologies (CMO, VT, LPT), both %Syn and %Name are notably low. For instance, using the bi-encoder top-1 setting, over 80% of generated aliases serve as new lexical bridges, successfully providing diverse surface forms that the curated ontologies lack.

Pseudo pair accuracy. LLM-based aliases are effective because they create lexical bridges, but they do not work reliably on their own because the raw alias drifts. However, our ontology-aware filter can remove drift. To evaluate the filter's effectiveness on our generated pseudo pairs, we compare against NCBI and BC5CDR, which provide gold labels for the training data. A pseudo-labeled sample is counted as correct whenever its assigned entity matches the gold label. Table 3 demonstrates that raw LLM alias generation (P_{Gen}`w/o filter`) includes noise, yielding a pseudo-label accuracy of 72% across both datasets. After removing drifted aliases (P_{Gen}), pseudo pair accuracy rises to over 90% (90.32% for NCBI and 91.40% for BC5CDR)

6.5.2 Retriever

Table 4 presents the retriever's performance, evaluated by overall Recall@64. A key finding is that fine-tuning consistently improves results across all benchmarks. The magnitude of this improvement is heavily dependent on the dataset's inherent synonym density. On synonym-rich datasets like NCBI and BC5CDR, the non-fine-tuned backbone is already robust, resulting in relatively small fine-tuning gains (+2.68% and +0.35%, respectively). On synonym-sparse animal science datasets (CMO, VT, and LPT), our ontology-aware fine-tuning delivers substantial improvements of +13.35% , +16.06% , and +23.96%, respectively.

When comparing the negative-sampling strategies under the Sci-ZSEL + Synonym framework, PC-POS emerges as the most effective approach overall, achieving the highest Recall@64 on NCBI, BC5CDR, Animal Science (CMO), and Animal Science (LPT). The sole exception is the Animal Science (VT) dataset, where RM-PCS achieves the peak performance (88.69%). This deviation suggests that, for VT's specific ontological structure, removing sibling entities from negative samples (RM-PCS) yields a stronger signal than adding neighbor entities as positive samples (PC-POS). The MRR follows a similar trend, with PC-POS winning the majority of benchmarks and RM-PCS winning in Animal Science (VT). Ultimately, these results confirm that integrating ontology structure into training sample construction is consistently superior to vanilla construction.

6.5.3 Reranker

Table 5 presents the reranker results. Fine-tuning improves overall Recall@1 and MRR across every dataset and backbone architecture, where we observe the following major trends:

When utilizing the BLINK backbone, the combined Sci-ZSEL + Synonym approach is clearly the most robust, achieving the highest overall Recall@1 across all five benchmarks. The MRR results closely follow this trend, with Sci-ZSEL + Synonym dominating four of the five datasets. The single exception is the Animal Science (VT) dataset, where the standalone Synonym setting holds a marginal lead of +0.17% in MRR. For the ReS backbone, the results are more nuanced. Sci-ZSEL + Synonym remains the dominant set-

Dataset	Setting	BLINK					ReS				
		Overall	MRR	HO	LO	NO	Overall	MRR	HO	LO	NO
NCBI	No fine-tune	64.38$_{\pm 0.00}$	72.39$_{\pm 0.00}$	**93.83**$_{\pm 0.00}$	64.12$_{\pm 0.00}$	23.64$_{\pm 0.00}$	45.94$_{\pm 0.00}$	58.41$_{\pm 0.00}$	67.53$_{\pm 0.00}$	44.44$_{\pm 0.00}$	18.64$_{\pm 0.00}$
	Sci-ZSEL w/o filter	70.69$_{\pm 0.58}$	77.65$_{\pm 0.47}$	92.75$_{\pm 0.19}$	66.44$_{\pm 1.22}$	48.18$_{\pm 0.79}$	60.28$_{\pm 0.42}$	73.57$_{\pm 0.27}$	68.72$_{\pm 0.68}$	59.41$_{\pm 1.88}$	50.15$_{\pm 3.19}$
	Sci-ZSEL	71.88$_{\pm 0.42}$	78.48$_{\pm 0.35}$	92.86$_{\pm 0.00}$	68.90$_{\pm 1.05}$	48.33$_{\pm 0.27}$	63.06$_{\pm 2.25}$	73.00$_{\pm 2.50}$	73.05$_{\pm 1.17}$	68.52$_{\pm 2.34}$	38.33$_{\pm 6.45}$
	Synonym	76.18$_{\pm 0.24}$	83.17$_{\pm 0.49}$	93.18$_{\pm 0.33}$	73.23$_{\pm 0.58}$	58.18$_{\pm 2.08}$	**78.09**$_{\pm 0.73}$	**84.59**$_{\pm 0.37}$	**93.94**$_{\pm 2.40}$	**74.07**$_{\pm 0.70}$	**63.79**$_{\pm 1.89}$
	Sci-ZSEL + Synonym	**77.43**$_{\pm 0.67}$	**84.35**$_{\pm 0.74}$	92.75$_{\pm 1.50}$	**74.54**$_{\pm 2.06}$	**61.67**$_{\pm 1.15}$	70.52$_{\pm 1.02}$	79.11$_{\pm 1.58}$	74.24$_{\pm 1.46}$	71.30$_{\pm 0.24}$	**63.79**$_{\pm 3.09}$
BC5CDR	No fine-tune	74.36$_{\pm 0.00}$	79.53$_{\pm 0.00}$	**96.26**$_{\pm 0.00}$	66.77$_{\pm 0.00}$	22.43$_{\pm 0.00}$	32.65$_{\pm 0.00}$	45.34$_{\pm 0.00}$	39.86$_{\pm 0.00}$	35.61$_{\pm 0.00}$	12.42$_{\pm 0.00}$
	Sci-ZSEL w/o filter	78.14$_{\pm 0.47}$	83.90$_{\pm 0.36}$	94.94$_{\pm 0.64}$	61.55$_{\pm 1.31}$	44.45$_{\pm 1.04}$	68.14$_{\pm 0.76}$	77.01$_{\pm 0.67}$	82.77$_{\pm 0.53}$	51.04$_{\pm 2.87}$	40.31$_{\pm 1.32}$
	Sci-ZSEL	79.16$_{\pm 0.58}$	84.40$_{\pm 0.27}$	96.01$_{\pm 0.31}$	72.17$_{\pm 2.03}$	39.88$_{\pm 1.45}$	76.91$_{\pm 0.53}$	82.52$_{\pm 0.28}$	**94.83**$_{\pm 0.58}$	64.65$_{\pm 1.58}$	37.85$_{\pm 1.42}$
	Synonym	78.20$_{\pm 1.24}$	83.49$_{\pm 1.88}$	96.17$_{\pm 0.24}$	67.97$_{\pm 1.93}$	37.85$_{\pm 3.51}$	74.74$_{\pm 0.40}$	80.15$_{\pm 0.48}$	94.12$_{\pm 0.44}$	58.68$_{\pm 3.04}$	34.09$_{\pm 0.83}$
	Sci-ZSEL + Synonym	**81.20**$_{\pm 0.58}$	**86.20**$_{\pm 0.48}$	95.96$_{\pm 0.30}$	**74.93**$_{\pm 1.96}$	**46.87**$_{\pm 1.30}$	**77.90**$_{\pm 0.12}$	**83.21**$_{\pm 0.26}$	94.78$_{\pm 0.17}$	**65.42**$_{\pm 2.49}$	**41.66**$_{\pm 0.66}$
CMO	No fine-tune	50.15$_{\pm 0.00}$	60.74$_{\pm 0.00}$	92.91$_{\pm 0.00}$	50.95$_{\pm 0.00}$	29.67$_{\pm 0.00}$	48.92$_{\pm 0.00}$	61.06$_{\pm 0.00}$	82.15$_{\pm 0.00}$	51.49$_{\pm 0.00}$	31.37$_{\pm 0.00}$
	Sci-ZSEL w/o filter	57.09$_{\pm 2.37}$	66.43$_{\pm 1.96}$	93.97$_{\pm 3.88}$	58.74$_{\pm 2.26}$	38.62$_{\pm 2.31}$	41.42$_{\pm 2.31}$	54.82$_{\pm 2.24}$	44.34$_{\pm 2.98}$	49.59$_{\pm 4.06}$	33.22$_{\pm 4.05}$
	Sci-ZSEL	56.89$_{\pm 0.48}$	67.15$_{\pm 0.34}$	93.16$_{\pm 0.42}$	56.89$_{\pm 0.14}$	**40.09**$_{\pm 1.08}$	56.84$_{\pm 1.46}$	66.72$_{\pm 1.46}$	96.74$_{\pm 0.79}$	58.43$_{\pm 1.97}$	**37.03**$_{\pm 2.98}$
	Synonym	57.59$_{\pm 1.72}$	66.50$_{\pm 1.51}$	93.15$_{\pm 0.25}$	62.79$_{\pm 2.24}$	36.77$_{\pm 2.34}$	**58.48**$_{\pm 0.37}$	**68.29**$_{\pm 0.36}$	94.70$_{\pm 0.51}$	64.91$_{\pm 0.41}$	36.32$_{\pm 1.09}$
	Sci-ZSEL + Synonym	**58.88**$_{\pm 3.30}$	**67.72**$_{\pm 2.92}$	**94.87**$_{\pm 0.65}$	**65.22**$_{\pm 2.99}$	36.88$_{\pm 5.58}$	57.43$_{\pm 0.23}$	66.95$_{\pm 0.12}$	**96.99**$_{\pm 0.79}$	**65.54**$_{\pm 0.36}$	32.31$_{\pm 0.91}$
VT	No fine-tune	43.13$_{\pm 0.00}$	56.38$_{\pm 0.00}$	97.32$_{\pm 0.00}$	48.70$_{\pm 0.00}$	31.43$_{\pm 0.00}$	38.33$_{\pm 0.00}$	51.14$_{\pm 0.00}$	95.97$_{\pm 0.00}$	54.61$_{\pm 0.00}$	19.71$_{\pm 0.00}$
	Sci-ZSEL w/o filter	38.29$_{\pm 1.21}$	54.51$_{\pm 0.74}$	97.32$_{\pm 0.00}$	50.90$_{\pm 2.58}$	21.64$_{\pm 0.94}$	45.81$_{\pm 2.13}$	59.78$_{\pm 0.86}$	97.32$_{\pm 0.00}$	64.12$_{\pm 5.84}$	26.94$_{\pm 0.40}$
	Sci-ZSEL	46.64$_{\pm 0.54}$	60.04$_{\pm 0.26}$	97.32$_{\pm 0.00}$	49.68$_{\pm 0.96}$	37.00$_{\pm 0.43}$	41.15$_{\pm 0.42}$	53.98$_{\pm 0.38}$	97.32$_{\pm 0.00}$	59.88$_{\pm 1.50}$	21.30$_{\pm 0.76}$
	Synonym	70.83$_{\pm 0.42}$	**79.66**$_{\pm 0.73}$	97.54$_{\pm 0.39}$	**76.64**$_{\pm 1.40}$	63.24$_{\pm 1.32}$	62.78$_{\pm 3.91}$	73.65$_{\pm 3.55}$	96.87$_{\pm 0.39}$	67.54$_{\pm 0.61}$	54.67$_{\pm 6.58}$
	Sci-ZSEL + Synonym	**71.25**$_{\pm 2.58}$	79.49$_{\pm 1.65}$	**97.77**$_{\pm 0.77}$	76.46$_{\pm 2.47}$	**64.04**$_{\pm 3.43}$	**65.58**$_{\pm 2.62}$	**75.76**$_{\pm 2.03}$	**97.77**$_{\pm 0.77}$	**74.09**$_{\pm 4.31}$	**55.53**$_{\pm 2.90}$
LPT	No fine-tune	57.34$_{\pm 0.00}$	63.29$_{\pm 0.00}$	94.59$_{\pm 0.00}$	78.29$_{\pm 0.00}$	20.62$_{\pm 0.00}$	59.70$_{\pm 0.00}$	67.91$_{\pm 0.00}$	92.34$_{\pm 0.00}$	77.71$_{\pm 0.00}$	27.69$_{\pm 0.00}$
	Sci-ZSEL w/o filter	54.62$_{\pm 1.06}$	61.67$_{\pm 0.85}$	95.05$_{\pm 0.46}$	72.00$_{\pm 2.29}$	17.64$_{\pm 1.45}$	55.82$_{\pm 0.64}$	64.20$_{\pm 0.84}$	93.54$_{\pm 2.03}$	68.95$_{\pm 1.44}$	22.97$_{\pm 0.89}$
	Sci-ZSEL	58.22$_{\pm 0.29}$	64.18$_{\pm 0.19}$	95.35$_{\pm 0.52}$	**79.81**$_{\pm 1.43}$	21.23$_{\pm 0.62}$	62.14$_{\pm 0.81}$	69.71$_{\pm 0.60}$	94.29$_{\pm 0.26}$	80.38$_{\pm 1.32}$	30.36$_{\pm 0.99}$
	Synonym	78.81$_{\pm 1.92}$	84.56$_{\pm 1.60}$	97.90$_{\pm 0.26}$	79.43$_{\pm 0.57}$	65.44$_{\pm 4.20}$	77.93$_{\pm 1.53}$	83.75$_{\pm 1.14}$	95.05$_{\pm 0.46}$	77.14$_{\pm 0.57}$	66.67$_{\pm 3.40}$
	Sci-ZSEL + Synonym	**80.70**$_{\pm 0.21}$	**86.12**$_{\pm 0.12}$	**98.05**$_{\pm 0.26}$	79.05$_{\pm 3.15}$	**69.74**$_{\pm 1.28}$	**81.21**$_{\pm 2.29}$	**86.21**$_{\pm 1.38}$	**97.45**$_{\pm 0.52}$	**80.95**$_{\pm 1.19}$	**70.26**$_{\pm 4.48}$

Table 5: A performance comparison of BLINK and ReS rerankers across all five benchmarks. The Recall@1 reported as "Overall" where the score considers the entire dataset, while HO, LO, and NO show category-wise scores. **Bold** indicates the best results when comparing row-wise.

ting for BC5CDR, Animal Science (VT), and Animal Science (LPT). However, on the NCBI and Animal Science (CMO) benchmarks, the Synonym setting performs best, outperforming the combined approach in Recall@1 by +7.57% and +1.05%, respectively. The MRR results for the ReS backbone mirror this exact trend, with the Synonym baseline maintaining its lead on those same two datasets.

Most notably, Sci-ZSEL excels in the highly challenging NO cases. Fine-tuning drives massive improvements in ZSEL, frequently doubling or tripling the non-fine-tuned backbone performance. On the animal science datasets (specifically VT and LPT), we observe striking absolute gains of 30% to nearly 50% in the NO category.

Collectively, these findings confirm that Sci-ZSEL effectively addresses a primary challenge of scientific EL. By utilizing LLM-generated aliases, the model successfully captures highly divergent surface forms, providing critical, complementary supervision that manually curated ontology synonyms alone cannot supply.

6.6 Ablation Study: Effect of Removing the Filter

To verify the necessity of the ontology-aware filter, we evaluate the impact of omitting it (Sci-ZSEL w/o filter). Removing the filter often harms model performance, causing the reranker performance (Table 5) to drop below the non-fine-tuned baseline across several datasets and backbone combinations. The largest drop of overall Recall@1 is 7.50% in Animal Science (CMO) using ReS. The drop in performance occurs because drifted aliases train the model to link mentions to the neighboring entity rather than their true referent. As a result, performance drops even on the easiest HO cases (the largest drop of HO Recall@1 is 37.81%). These effects are observed severely in animal science datasets. We conclude that the ontology-aware filter is necessary to successfully leverage LLM-based aliases, especially in low-resource settings.

7 Conclusion

In conclusion, this paper offers a cost-aware solution to severe lexical divergence in scientific entity linking. We introduce Sci-ZSEL, a zero-shot framework that bounds LLM alias generation to selected entities and employs an ontology-aware filter to discard drifted aliases. To evaluate this, we also release a challenging, high-divergence animal science benchmark (CMO, VT, LPT). Across five datasets, Sci-ZSEL significantly outperforms non-fine-tuned baselines, achieving absolute gains in the lexically divergent domain. We demonstrate that combining Sci-ZSEL with curated synonyms yields the most robust reranker configuration, and our ablation studies confirm the ontology-aware filter is essential to prevent LLM noise from degrading accuracy below baseline levels. Ultimately, this work provides a scalable, reusable blueprint for zero-shot adaptation in specialized, low-resource scientific domains.

8 Limitations

While Sci-ZSEL demonstrates strong performance in scientific entity linking, it is subject to several limitations. First, the framework relies heavily on the domain knowledge of the underlying LLM (Llama 3.2 3B Instruct in our experiments) to generate pseudo pairs. An LLM with weaker biomedical or animal science coverage would produce noisier, more drifted aliases, thereby increasing the burden on the filtering module. Additionally, future adaptations relying on closed-source LLMs could face reproducibility risks if silent updates arbitrarily alter alias distributions. Second, our current framework and evaluation are strictly limited to English. The benchmark datasets, prompt templates, filtering model (BioLORD), and reranking backbones (BLINK, ReS) are all predominantly English-centric. Extending this approach to other languages would require multilingual LLMs and semantic-similarity models specifically tailored to the biomedical domain, which are not currently available off-the-shelf.

Furthermore, the generated pseudo pairs and filtering decisions are intrinsically tied to fixed snapshots of the target ontologies (Appendix Table 8). Because ontologies are continuously updated with obsolete entries retired and hierarchical structures, such as the neighbor sets $\mathcal{N}(e)$ and $\mathcal{N}^{+}(e)$, frequently modified—any update to a target ontology requires Sci-ZSEL to regenerate the aliases and rerun the filtering process to avoid stale supervision. Finally, our current framework does not handle "NIL" entities, which are mentions lacking a valid referent in the target ontology. Although our new animal science benchmark reveals that a significant portion of mentions cannot be linked to all three ontologies, these NIL cases were excluded from our current evaluation. Developing a robust mechanism to identify and manage unlinkable mentions remains a critical practical challenge that we leave for future work.

9 Ethical considerations

Annotation process and compensation. The animal science benchmark (Section 3) was developed by a team comprising one boundary annotator, four graduate-student linking annotators, and one domain-expert curator who was responsible for resolving disagreements. All source texts were derived entirely from publicly available PubMed abstracts, ensuring that the dataset contains no personally identifiable information (PII).

LLM usage disclosure. To generate entity aliases (Section 5.2), we utilized Llama 3.2 3B Instruct, an open-weights large language model. The LLM was prompted strictly using entity definitions sourced from public ontologies; at no point was human-generated or private data processed by the model. All other system components (BLINK, ReS, and BioLORD) are open-source and were deployed in strict adherence to their published usage licenses.

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A Appendix

A.1 Entity Generation Prompt

We use a single prompt template across all five datasets, varying only the domain string and the three in-context examples, both of which are drawn from the target ontology. The template combines a system message specifying the domain expertise with a user message containing the definition to be named:

```
[System] You are a specialist in
{domain} terminology. Given an entity's
definition, generate a scientifically
accurate name that best represents its
meaning.


Guidelines:
1.  Carefully interpret the semantic
content of the "definition".
2. Generate a precise name that:
  - Accurately reflects the definition.
  - Aligns with standard terminology in
{domain}.


Example 1
Definition: {def1}
Generated name: {name1}


Example 2
Definition: {def2}
Generated name: {name2}


Example 3
Definition: {def3}
Generated name: {name3}


[User] Definition : {definition}
Return all possible names for this
definition, separated by commas. Do not
include any additional text.
```

The domain string is *biomedical disease* for NCBI Disease, *biomedical Disease and biomedical Chemical* for BC5CDR, and *animal science* for CMO, VT, and LPT. The three in-context examples used for each ontology are listed in Table 12.

A.2 Number of Training Samples

Table 6 reports the number of pseudo-labeled pairs used for retriever and reranker fine-tuning under each setting. The number of samples (SMPL) vary by an order of magnitude across cells, driven by two factors: curated synonym density (Synonym yields 3,283 (NCBI), 4,676 (BC5CDR), 871 (CMO), 1,854 (VT), and 477 (LPT) pairs, tracking the synonym/entity ratios in Table 1 (ontology block)) and filter discard rate (Sci-ZSEL retains 74% (NCBI), 77% (BC5CDR), 64% (CMO), 29% (VT), and 22% (LPT) of unfiltered pairs, suggesting that the filter removes a larger fraction of generated aliases for the animal science ontologies. Sci-ZSEL +Synonym is the largest set across all benchmarks.

Setting	NCBI	BC5CDR	CMO	VT	LPT
Sci-ZSEL w/o filter	1757	7447	2513	1305	1592
Sci-ZSEL	1301	5766	1614	381	352
Synonym	3283	4676	871	1854	477
Sci-ZSEL + Synonym	4584	6222	1825	2134	694

Table 6: Number of training samples (SMPL) per (dataset, setting) used for fine-tuning.

A.3 Bi-encoder Details

A.3.1 Architecture

Following Wu et al. (2020), our bi-encoder uses two independent BERT transformers T_m and T_e to embed the mention context and the entity into a shared dense space. The mention input is

$$\tau_m = [\text{CLS}]\ \text{ctx}_l\ [\text{Ms}]\ m\ [\text{Me}]\ \text{ctx}_r\ [\text{SEP}] \quad (11)$$

and the entity input is

$$\tau_e = [\text{CLS}]\ \text{title}_e\ [\text{ENT}]\ \text{desc}_e\ [\text{SEP}] \quad (12)$$

where $\text{ctx}_l, \text{ctx}_r$ are the left and right contexts around m, and $\text{title}_e, \text{desc}_e$ are the entity title and description. Each sequence is encoded independently and the `[CLS]` output is taken as its dense representation:

$$y_m = \text{red}(T_m(\tau_m)) \quad (13)$$

$$y_e = \text{red}(T_e(\tau_e)) \quad (14)$$

The mention–entity score is the dot product

$$s(m, e) = y_m \cdot y_e \quad (15)$$

The bi-encoder is initialized from the BLINK weights of Wu et al. (2020) and fine-tuned on our pseudo-labeled pairs.

A.3.2 Negative-sampling Formal Definitions

Notation. Let $B = \{m_1, \ldots, m_b\}$ be a training batch of b mentions with gold entities $\{e_1, \ldots, e_b\} \subset \mathcal{E}$. For each batch we construct a candidate column set $C = G \cup R$, where G is the set of unique golds in the batch and R is a set of random entities sampled uniformly from $\mathcal{E} \setminus G$.

Because the same gold entity may appear for multiple mentions in a batch, removing gold entities from the negative set can reduce the number of available in-batch negatives. We therefore add random entities R sampled from $\mathcal{E} \setminus G$ to keep the number of candidate negatives approximately stable. We reuse $\mathcal{N}(e)$ and $\mathcal{N}^+(e)$ from Section 5.2.2. For each row i with gold e_i, the positive set $\mathcal{P}_i$ and negative set $\mathcal{N}_i$ are defined per strategy in Table 7.

Strategy	Positive set $\mathcal{P}_i$	Negative set $\mathcal{N}_i$
BASE	$\{e_i\}$	$(G \setminus \{e_i\}) \cup R$
RM-PCS	$\{e_i\}$	$\big((G \setminus \{e_i\}) \cup R\big) \setminus \mathcal{N}^+(e_i)$
PC-POS	$\{e_i\} \cup (\mathcal{N}(e_i) \cap G)$	$\big((G \setminus \mathcal{P}_i) \cup R\big) \setminus \mathcal{N}(e_i)$

Table 7: Per-row positive set $\mathcal{P}_i$ and negative set $\mathcal{N}_i$ for the three negative-sampling strategies. $\mathcal{N}(e_i) = \text{parents}(e_i) \cup \text{children}(e_i)$; $\mathcal{N}^+(e_i) = \mathcal{N}(e_i) \cup \text{siblings}(e_i)$. Siblings are not promoted as positives in PC-POS, preserving sibling separation pressure.

Sampling budget. Naively sampling $|R| = b - |G|$ leaves $\mathcal{N}_i$ short whenever RM-PCS or PC-POS discards neighbors. To keep the per-row negative count stable, we sample $|R| = (b - |G|) + \min(\max_i |\mathcal{N}^+(e_i)|, H_{\text{cap}})$ with $H_{\text{cap}} = 30$, then truncate each row's $\mathcal{N}_i$ to the target budget.

A.3.3 Training Objective

Following the in-batch cross-entropy objective of Wu et al. (2020), for each row i the loss is

$$\mathcal{L}_i = -\frac{1}{|\mathcal{P}_i|} \sum_{p \in \mathcal{P}_i} \log \frac{\exp s(m_i, p)}{Z_i(p)} \tag{16}$$

where the partition function is

$$Z_i(p) = \exp s(m_i, p) + \sum_{c \in \mathcal{N}_i} \exp s(m_i, c)$$

For BASE and RM-PCS, $|\mathcal{P}_i| = 1$ and the expression reduces to the standard BLINK in-batch cross-entropy loss; for PC-POS, the average is taken over multiple positives against the same negative set. The full batch loss is

$$\mathcal{L} = \frac{1}{b} \sum_{i=1}^{b} \mathcal{L}_i. \tag{17}$$

A.4 Cross-encoder Details

A.4.1 Architecture

We evaluate two cross-encoder backbones, BLINK (Wu et al., 2020) and ReS (Xu et al., 2023b). Both share the same concatenated mention–entity input:

$$\begin{aligned}\tau_{m,e} = &[\text{CLS}]\ \text{ctx}_l\ [\text{Ms}]\ m\ [\text{Me}]\ \text{ctx}_r\ [\text{SEP}] \\ &\text{title}_e\ [\text{ENT}]\ \text{desc}_e\ [\text{SEP}],\end{aligned} \tag{18}$$

where $\text{ctx}_l, \text{ctx}_r$ are the left and right contexts around m, and $\text{title}_e, \text{desc}_e$ are the entity title and description.

BLINK cross-encoder. Following Wu et al. (2020), a single BERT transformer T_{cross} jointly encodes $\tau_{m,e}$, and the score is a linear projection of the reduced [CLS] embedding:

$$y_{m,e} = \text{red}(T_{\text{cross}}(\tau_{m,e})) \tag{19}$$

$$s_{\text{BLINK}}(m, e) = \mathbf{w}^\top y_{m,e} \tag{20}$$

where $\mathbf{w}$ is a learned scoring vector. The BLINK reranker is initialized from the cross-encoder weights of Wu et al. (2020) pretrained on Wikipedia entity linking.

ReS cross-encoder. The Read-and-Select framework (Xu et al., 2023b) factors scoring into two stages. In the *reading* stage, each candidate $e \in \mathcal{C}(m)$ is encoded with the mention by a cross-encoder T_{read} to produce a candidate-conditioned mention representation h_m^e. In the *selecting* stage, the $|\mathcal{C}(m)|$ representations are passed through a candidate-level transformer that performs cross-candidate attention, so the score for e depends on the other candidates in $\mathcal{C}(m)$ rather than on e alone:

$$s_{\text{ReS}}(m, e) = f_{\text{sel}}\big(\{h_m^{e'}\}_{e' \in \mathcal{C}(m)},\ e\big) \tag{21}$$

where f_{sel} is the selecting head; see Xu et al. (2023b) for the full architecture. The ReS reranker is initialized from the released ReS weights.

A.4.2 Candidate Set Construction

For each pseudo pair $\langle m, e \rangle$, let $\{c_1, \ldots, c_K\}$ be the top-K candidates from the BLINK bi-encoder, ranked by retriever score. The reranker candidate set $\mathcal{C}(m)$ equals $\{c_1, \ldots, c_K\}$ when $e \in \{c_1, \ldots, c_K\}$, and otherwise replaces the lowest-ranked candidate with e, giving $\{c_1, \ldots, c_{K-1}, e\}$. This guarantees $e \in \mathcal{C}(m)$ and $|\mathcal{C}(m)| = K$ throughout training.

A.4.3 Training Objective

For each pseudo pair $\langle m, e \rangle$ with candidate set $\mathcal{C}(m)$, the reranker is trained with cross-entropy,

treating e as the positive and the remaining candidates as negatives:

$$\mathcal{L} = -\log \frac{\exp s(m, e)}{\sum_{c \in \mathcal{C}(m)} \exp s(m, c)} \tag{22}$$

where $s(m, c)$ is the reranker score (s_{BLINK} or s_{ReS}). The same objective is used for both backbones; only the scoring function differs.

A.5 Training Hyperparameters and Hardware

Hardware. LLM alias generation uses Llama 3.2 3B Instruct on a single NVIDIA A100. Retriever and reranker fine-tuning use four A100s.

Bi-encoder retriever. The BLINK retriever uses `bert-large-uncased` with a 128-token mention context and 128-token candidate. It is trained at a learning rate of 2×10^{-5} with batch size 512, falling back to 128 when fewer than 512 training pairs are available.

Cross-encoder rerankers. The BLINK reranker uses `bert-large-uncased` with a 64-token context and 128-token candidate, trained at learning rate 2×10^{-5} with batch size 32. The ReS reranker uses `roberta-base` with a 256-token context and 256-token entity description, trained at learning rate 1×10^{-4} with batch size 8. Dropout is fixed at 0.2 throughout.

Epochs and reporting protocol. Because the zero-shot setting provides no validation set, best-epoch selection is not possible; we fix the number of epochs in advance and report results from the last epoch. The retriever runs for 4 epochs on BC5CDR (the largest dataset) and 1 epoch on the remaining four datasets. The reranker runs for 3 epochs on all benchmarks. Empirical loss curves confirm that the chosen epoch counts place the final epoch at or near the training optimum across all benchmarks, validating our last-epoch reporting protocol.

A.6 Ontology/Knowledge Base Versions

Table 8 reports the specific releases of each knowledge base used in our experiments. Versions were fixed at the start of experimentation and reused across all settings.

KB / Ontology	Used by	Release
MeSH 2025	BC5CDR	2025-01-01
MEDIC	NCBI Disease	2025-02-28
CMO	CMO EL Corpus	2026-02-28
VT	VT EL Corpus	2026-03-03
LPT	LPT EL Corpus	2025-08-14

Table 8: Release versions of the knowledge bases and ontologies used in this work.

Dataset	Setting	Overall	MRR	HO	LO	NO
NCBI	No fine-tune	$88.12_{\pm 0.00}$	$61.94_{\pm 0.00}$	$\mathbf{99.68}_{\pm 0.00}$	$92.82_{\pm 0.00}$	$62.73_{\pm 0.00}$
	Sci-ZSEL w/o filter	$87.74_{\pm 0.22}$	$62.48_{\pm 1.82}$	$99.46_{\pm 0.19}$	$91.67_{\pm 0.23}$	$63.64_{\pm 1.58}$
	Sci-ZSEL	$87.40_{\pm 0.47}$	$58.11_{\pm 2.28}$	$\mathbf{99.68}_{\pm 0.00}$	$90.97_{\pm 0.61}$	$63.18_{\pm 1.21}$
	Synonym	$89.20_{\pm 0.24}$	$\mathbf{64.53}_{\pm 2.28}$	$99.46_{\pm 0.38}$	$92.05_{\pm 0.35}$	$69.24_{\pm 0.95}$
	Sci-ZSEL + Synonym	$\mathbf{89.72}_{\pm 0.97}$	$64.35_{\pm 2.10}$	$\mathbf{99.68}_{\pm 0.00}$	$\mathbf{92.90}_{\pm 1.33}$	$\mathbf{69.54}_{\pm 1.64}$
BC5CDR	No fine-tune	$\mathbf{88.79}_{\pm 0.00}$	$73.91_{\pm 0.00}$	$99.46_{\pm 0.00}$	$\mathbf{96.09}_{\pm 0.00}$	$\mathbf{57.24}_{\pm 0.00}$
	Sci-ZSEL w/o filter	$88.41_{\pm 0.74}$	$\mathbf{74.09}_{\pm 1.22}$	$\mathbf{99.49}_{\pm 0.07}$	$95.52_{\pm 1.05}$	$55.88_{\pm 2.40}$
	Sci-ZSEL	$85.27_{\pm 1.75}$	$70.75_{\pm 2.08}$	$99.23_{\pm 0.23}$	$89.20_{\pm 3.75}$	$47.17_{\pm 4.53}$
	Synonym	$87.22_{\pm 0.16}$	$72.03_{\pm 0.26}$	$99.25_{\pm 0.10}$	$91.64_{\pm 1.08}$	$53.78_{\pm 0.45}$
	Sci-ZSEL + Synonym	$87.96_{\pm 0.48}$	$73.20_{\pm 0.33}$	$99.40_{\pm 0.04}$	$93.55_{\pm 1.01}$	$55.39_{\pm 1.60}$
CMO	No fine-tune	$75.74_{\pm 0.00}$	$43.20_{\pm 0.00}$	$99.27_{\pm 0.00}$	$87.43_{\pm 0.00}$	$55.04_{\pm 0.00}$
	Sci-ZSEL w/o filter	$\mathbf{89.96}_{\pm 0.23}$	$54.09_{\pm 2.73}$	$\mathbf{99.51}_{\pm 0.00}$	$97.48_{\pm 0.08}$	$\mathbf{79.24}_{\pm 0.47}$
	Sci-ZSEL	$89.22_{\pm 0.86}$	$56.06_{\pm 0.55}$	$\mathbf{99.51}_{\pm 0.00}$	$97.97_{\pm 0.24}$	$77.12_{\pm 2.16}$
	Synonym	$85.71_{\pm 0.40}$	$53.66_{\pm 0.89}$	$99.35_{\pm 0.14}$	$97.12_{\pm 0.39}$	$69.84_{\pm 0.54}$
	Sci-ZSEL + Synonym	$88.22_{\pm 0.89}$	$\mathbf{58.17}_{\pm 1.01}$	$\mathbf{99.51}_{\pm 0.00}$	$\mathbf{98.29}_{\pm 0.20}$	$74.56_{\pm 1.93}$
VT	No fine-tune	$72.63_{\pm 0.00}$	$34.67_{\pm 0.00}$	$\mathbf{99.33}_{\pm 0.00}$	$86.96_{\pm 0.00}$	$59.96_{\pm 0.00}$
	Sci-ZSEL w/o filter	$84.70_{\pm 0.96}$	$43.95_{\pm 1.20}$	$\mathbf{99.33}_{\pm 0.00}$	$96.64_{\pm 0.44}$	$75.31_{\pm 1.53}$
	Sci-ZSEL	$84.72_{\pm 1.69}$	$45.20_{\pm 0.90}$	$\mathbf{99.33}_{\pm 0.00}$	$\mathbf{96.75}_{\pm 0.40}$	$75.28_{\pm 2.73}$
	Synonym	$\mathbf{86.99}_{\pm 1.74}$	$\mathbf{47.83}_{\pm 4.78}$	$\mathbf{99.33}_{\pm 0.00}$	$93.22_{\pm 2.30}$	$\mathbf{81.36}_{\pm 1.82}$
	Sci-ZSEL + Synonym	$85.58_{\pm 4.10}$	$45.50_{\pm 15.06}$	$98.43_{\pm 1.55}$	$91.88_{\pm 4.37}$	$79.84_{\pm 4.55}$
LPT	No fine-tune	$68.70_{\pm 0.00}$	$51.17_{\pm 0.00}$	$\mathbf{100.00}_{\pm 0.00}$	$90.86_{\pm 0.00}$	$35.38_{\pm 0.00}$
	Sci-ZSEL w/o filter	$70.08_{\pm 0.28}$	$47.50_{\pm 0.96}$	$\mathbf{100.00}_{\pm 0.00}$	$93.33_{\pm 0.33}$	$37.13_{\pm 0.47}$
	Sci-ZSEL	$75.07_{\pm 1.54}$	$54.76_{\pm 0.14}$	$\mathbf{100.00}_{\pm 0.00}$	$\mathbf{96.19}_{\pm 0.33}$	$46.67_{\pm 3.46}$
	Synonym	$\mathbf{92.43}_{\pm 0.68}$	$\mathbf{75.56}_{\pm 0.87}$	$\mathbf{100.00}_{\pm 0.00}$	$91.05_{\pm 2.01}$	$\mathbf{88.00}_{\pm 0.62}$
	Sci-ZSEL + Synonym	$92.29_{\pm 0.44}$	$57.38_{\pm 1.37}$	$\mathbf{100.00}_{\pm 0.00}$	$92.19_{\pm 0.66}$	$87.08_{\pm 0.93}$

Table 9: Retriever Recall@64 under the **BASE** negative-sampling strategy. **Bold** represents the best results when comparing row-wise.

Dataset	Setting	Overall	MRR	HO	LO	NO
NCBI	No fine-tune	$88.12_{\pm 0.00}$	$61.94_{\pm 0.00}$	$\mathbf{99.68}_{\pm 0.00}$	$\mathbf{92.82}_{\pm 0.00}$	$62.73_{\pm 0.00}$
	Sci-ZSEL w/o filter	$87.01_{\pm 1.85}$	$63.75_{\pm 1.48}$	$98.70_{\pm 1.42}$	$90.67_{\pm 1.74}$	$63.48_{\pm 2.96}$
	Sci-ZSEL	$80.70_{\pm 11.97}$	$54.37_{\pm 10.62}$	$92.21_{\pm 12.94}$	$83.26_{\pm 13.97}$	$59.55_{\pm 6.70}$
	Synonym	$\mathbf{89.73}_{\pm 0.30}$	$63.99_{\pm 1.16}$	$\mathbf{99.68}_{\pm 0.00}$	$92.36_{\pm 1.16}$	$\mathbf{70.60}_{\pm 1.31}$
	Sci-ZSEL + Synonym	$89.41_{\pm 0.78}$	$\mathbf{64.41}_{\pm 1.94}$	$\mathbf{99.68}_{\pm 0.00}$	$91.66_{\pm 0.80}$	$\mathbf{70.60}_{\pm 2.15}$
BC5CDR	No fine-tune	$\mathbf{88.79}_{\pm 0.00}$	$\mathbf{73.91}_{\pm 0.00}$	$\mathbf{99.46}_{\pm 0.00}$	$\mathbf{96.09}_{\pm 0.00}$	$\mathbf{57.24}_{\pm 0.00}$
	Sci-ZSEL w/o filter	$88.21_{\pm 2.01}$	$73.51_{\pm 2.57}$	$99.42_{\pm 0.23}$	$95.39_{\pm 3.00}$	$55.30_{\pm 6.11}$
	Sci-ZSEL	$85.41_{\pm 0.27}$	$70.29_{\pm 0.66}$	$99.29_{\pm 0.15}$	$89.20_{\pm 1.98}$	$47.63_{\pm 2.14}$
	Synonym	$87.13_{\pm 0.59}$	$72.24_{\pm 0.58}$	$99.34_{\pm 0.19}$	$91.87_{\pm 0.86}$	$53.08_{\pm 2.85}$
	Sci-ZSEL + Synonym	$86.61_{\pm 2.16}$	$68.05_{\pm 7.57}$	$99.00_{\pm 0.56}$	$90.18_{\pm 5.00}$	$52.75_{\pm 4.63}$
CMO	No fine-tune	$75.74_{\pm 0.00}$	$43.20_{\pm 0.00}$	$99.27_{\pm 0.00}$	$87.43_{\pm 0.00}$	$55.04_{\pm 0.00}$
	Sci-ZSEL w/o filter	$88.02_{\pm 1.24}$	$54.37_{\pm 1.05}$	$\mathbf{99.51}_{\pm 0.00}$	$95.68_{\pm 2.39}$	$76.29_{\pm 0.86}$
	Sci-ZSEL	$88.06_{\pm 0.25}$	$56.00_{\pm 0.95}$	$\mathbf{99.51}_{\pm 0.00}$	$97.97_{\pm 0.24}$	$74.44_{\pm 0.51}$
	Synonym	$85.47_{\pm 0.49}$	$53.47_{\pm 0.35}$	$99.27_{\pm 0.00}$	$97.07_{\pm 0.16}$	$69.35_{\pm 1.05}$
	Sci-ZSEL + Synonym	$\mathbf{89.03}_{\pm 1.68}$	$\mathbf{57.17}_{\pm 0.99}$	$\mathbf{99.51}_{\pm 0.00}$	$\mathbf{98.33}_{\pm 0.34}$	$\mathbf{76.37}_{\pm 3.58}$
VT	No fine-tune	$72.63_{\pm 0.00}$	$34.67_{\pm 0.00}$	$\mathbf{99.33}_{\pm 0.00}$	$86.96_{\pm 0.00}$	$59.96_{\pm 0.00}$
	Sci-ZSEL w/o filter	$84.52_{\pm 1.08}$	$44.05_{\pm 0.51}$	$\mathbf{99.33}_{\pm 0.00}$	$96.41_{\pm 0.36}$	$75.14_{\pm 1.79}$
	Sci-ZSEL	$85.51_{\pm 0.30}$	$43.49_{\pm 0.72}$	$\mathbf{99.33}_{\pm 0.00}$	$\mathbf{96.64}_{\pm 0.44}$	$76.73_{\pm 0.26}$
	Synonym	$86.79_{\pm 2.67}$	$46.21_{\pm 3.65}$	$\mathbf{99.33}_{\pm 0.00}$	$93.04_{\pm 3.31}$	$81.12_{\pm 2.81}$
	Sci-ZSEL + Synonym	$\mathbf{88.69}_{\pm 2.22}$	$\mathbf{49.50}_{\pm 4.52}$	$\mathbf{99.33}_{\pm 0.00}$	$94.32_{\pm 3.26}$	$\mathbf{83.68}_{\pm 1.95}$
LPT	No fine-tune	$68.70_{\pm 0.00}$	$51.17_{\pm 0.00}$	$\mathbf{100.00}_{\pm 0.00}$	$90.86_{\pm 0.00}$	$35.38_{\pm 0.00}$
	Sci-ZSEL w/o filter	$70.82_{\pm 0.97}$	$48.46_{\pm 1.21}$	$\mathbf{100.00}_{\pm 0.00}$	$93.71_{\pm 0.58}$	$38.57_{\pm 1.85}$
	Sci-ZSEL	$76.87_{\pm 0.73}$	$54.03_{\pm 1.07}$	$\mathbf{100.00}_{\pm 0.00}$	$\mathbf{95.24}_{\pm 1.19}$	$51.18_{\pm 2.00}$
	Synonym	$91.83_{\pm 0.42}$	$\mathbf{75.45}_{\pm 1.19}$	$\mathbf{100.00}_{\pm 0.00}$	$90.10_{\pm 1.84}$	$87.18_{\pm 0.35}$
	Sci-ZSEL + Synonym	$\mathbf{92.48}_{\pm 0.35}$	$57.37_{\pm 0.59}$	$\mathbf{100.00}_{\pm 0.00}$	$92.57_{\pm 1.14}$	$\mathbf{87.28}_{\pm 0.17}$

Table 10: Retriever Recall@64 under the **RM-PCS** negative-sampling strategy. **Bold** represents the best results when comparing row-wise.

Dataset	Setting	Overall	MRR	HO	LO	NO
NCBI	No fine-tune	$88.12_{\pm 0.00}$	$61.94_{\pm 0.00}$	$\mathbf{99.68}_{\pm 0.00}$	$\mathbf{92.82}_{\pm 0.00}$	$62.73_{\pm 0.00}$
	Sci-ZSEL w/o filter	$88.75_{\pm 0.36}$	$63.78_{\pm 1.61}$	$99.46_{\pm 0.19}$	$92.21_{\pm 0.53}$	$66.97_{\pm 2.89}$
	Sci-ZSEL	$87.81_{\pm 0.63}$	$61.12_{\pm 1.48}$	$\mathbf{99.68}_{\pm 0.00}$	$91.82_{\pm 0.93}$	$63.33_{\pm 0.95}$
	Synonym	$90.21_{\pm 0.36}$	$65.20_{\pm 0.97}$	$99.35_{\pm 0.33}$	$91.98_{\pm 0.48}$	$73.94_{\pm 0.26}$
	Sci-ZSEL + Synonym	$\mathbf{90.80}_{\pm 0.87}$	$\mathbf{66.63}_{\pm 1.46}$	$99.46_{\pm 0.38}$	$91.98_{\pm 0.48}$	$\mathbf{76.37}_{\pm 2.36}$
BC5CDR	No fine-tune	$88.79_{\pm 0.00}$	$73.91_{\pm 0.00}$	$99.46_{\pm 0.00}$	$96.09_{\pm 0.00}$	$57.24_{\pm 0.00}$
	Sci-ZSEL w/o filter	$88.93_{\pm 1.03}$	$73.76_{\pm 1.74}$	$\mathbf{99.53}_{\pm 0.04}$	$\mathbf{96.19}_{\pm 1.62}$	$57.54_{\pm 3.34}$
	Sci-ZSEL	$87.80_{\pm 0.74}$	$72.63_{\pm 0.97}$	$99.42_{\pm 0.10}$	$94.60_{\pm 1.50}$	$54.09_{\pm 2.09}$
	Synonym	$88.57_{\pm 0.50}$	$73.50_{\pm 0.51}$	$99.48_{\pm 0.05}$	$95.50_{\pm 0.62}$	$56.58_{\pm 2.24}$
	Sci-ZSEL + Synonym	$\mathbf{89.14}_{\pm 0.65}$	$\mathbf{74.05}_{\pm 0.46}$	$99.29_{\pm 0.20}$	$95.60_{\pm 1.58}$	$\mathbf{59.38}_{\pm 1.69}$
CMO	No fine-tune	$75.74_{\pm 0.00}$	$43.20_{\pm 0.00}$	$99.27_{\pm 0.00}$	$87.43_{\pm 0.00}$	$55.04_{\pm 0.00}$
	Sci-ZSEL w/o filter	$\mathbf{89.24}_{\pm 1.61}$	$54.53_{\pm 1.76}$	$\mathbf{99.51}_{\pm 0.00}$	$96.89_{\pm 1.18}$	$\mathbf{78.07}_{\pm 2.77}$
	Sci-ZSEL	$88.34_{\pm 1.37}$	$54.79_{\pm 1.08}$	$\mathbf{99.51}_{\pm 0.00}$	$97.79_{\pm 0.16}$	$75.23_{\pm 3.14}$
	Synonym	$85.45_{\pm 0.91}$	$53.31_{\pm 0.96}$	$99.43_{\pm 0.14}$	$97.16_{\pm 0.41}$	$69.16_{\pm 1.71}$
	Sci-ZSEL + Synonym	$89.09_{\pm 1.57}$	$\mathbf{56.33}_{\pm 0.35}$	$\mathbf{99.51}_{\pm 0.00}$	$\mathbf{98.33}_{\pm 0.20}$	$76.52_{\pm 3.46}$
VT	No fine-tune	$72.63_{\pm 0.00}$	$34.67_{\pm 0.00}$	$\mathbf{99.33}_{\pm 0.00}$	$86.96_{\pm 0.00}$	$59.96_{\pm 0.00}$
	Sci-ZSEL w/o filter	$83.69_{\pm 0.94}$	$43.61_{\pm 0.66}$	$\mathbf{99.33}_{\pm 0.00}$	$96.23_{\pm 0.36}$	$73.79_{\pm 1.51}$
	Sci-ZSEL	$85.31_{\pm 1.03}$	$45.32_{\pm 0.93}$	$\mathbf{99.33}_{\pm 0.00}$	$\mathbf{96.70}_{\pm 0.30}$	$76.35_{\pm 1.67}$
	Synonym	$87.91_{\pm 2.22}$	$46.94_{\pm 2.40}$	$\mathbf{99.33}_{\pm 0.00}$	$93.33_{\pm 1.86}$	$82.92_{\pm 2.94}$
	Sci-ZSEL + Synonym	$\mathbf{87.99}_{\pm 1.47}$	$\mathbf{47.63}_{\pm 2.73}$	$\mathbf{99.33}_{\pm 0.00}$	$92.69_{\pm 3.08}$	$\mathbf{83.44}_{\pm 1.24}$
LPT	No fine-tune	$68.70_{\pm 0.00}$	$51.17_{\pm 0.00}$	$\mathbf{100.00}_{\pm 0.00}$	$90.86_{\pm 0.00}$	$35.38_{\pm 0.00}$
	Sci-ZSEL w/o filter	$71.01_{\pm 0.92}$	$50.47_{\pm 1.78}$	$\mathbf{100.00}_{\pm 0.00}$	$94.86_{\pm 1.51}$	$38.36_{\pm 1.24}$
	Sci-ZSEL	$76.18_{\pm 0.37}$	$54.01_{\pm 0.29}$	$\mathbf{100.00}_{\pm 0.00}$	$\mathbf{95.62}_{\pm 1.19}$	$49.44_{\pm 1.24}$
	Synonym	$91.78_{\pm 1.24}$	$\mathbf{75.72}_{\pm 0.62}$	$\mathbf{100.00}_{\pm 0.00}$	$90.28_{\pm 2.49}$	$86.97_{\pm 1.43}$
	Sci-ZSEL + Synonym	$\mathbf{92.66}_{\pm 0.69}$	$57.61_{\pm 0.65}$	$\mathbf{100.00}_{\pm 0.00}$	$93.14_{\pm 1.15}$	$\mathbf{87.38}_{\pm 0.93}$

Table 11: Retriever Recall@64 under the **PC-POS** negative-sampling strategy. **Bold** represents the best results when comparing row-wise.

Ontology	Definition	Generated name
NCBI	Autosomal dominant HEREDITARY CANCER SYNDROME in which a mutation most often in either BRCA1 or BRCA2 is associated with a significantly increased risk for breast and ovarian cancers.	Hereditary Breast and Ovarian Cancer Syndrome
	The presence in a cell of two paired chromosomes from the same parent, with no chromosome of that pair from the other parent. This chromosome composition stems from non-disjunction (NONDISJUNCTION, GENETIC) events during MEIOSIS. The disomy may be composed of both homologous chromosomes from one parent (heterodisomy) or a duplicate of one chromosome (isodisomy).	Uniparental Disomy
	Acquired, familial, and congenital disorders of SKELETAL MUSCLE and SMOOTH MUSCLE.	Muscular Diseases
BC5CDR	A benzamide derivative that is used as a dopamine antagonist.	Tiapride Hydrochloride
	Pathologic processes that affect patients after a surgical procedure. They may or may not be related to the disease for which the surgery was done, and they may or may not be direct results of the surgery.	Postoperative Complications
	Used with drugs and chemicals for experimental human and animal studies of their ill effects. It includes studies to determine the margin of safety or the reactions accompanying administration at various dose levels. It is used also for exposure to environmental agents. Poisoning should be considered for life-threatening exposure to environmental agents.	toxicity
CMO	Any measurement that deals with the process or development of a disease state, for example, the onset, progression or severity of the disease or its symptoms.	Disease process measurement
	The maximum arterial pressure within the cardiac cycle, i.e. at the point at which the heart is in its maximal state of contraction. This is the time when the blood is forced from the ventricles of the heart into the pulmonary artery and the aorta.	Systolic blood pressure
	Total distance around the body at the region of the body lateral to and including the hip joint or coxa.	Hip circumference
VT	Any measurable or observable characteristic related to the physical magnitude of the portion of the body containing the brain and organs of sight, hearing, taste, and smell.	Head size trait
	The distance between the surfaces of the superficial layer of solid, hard bone that covers spongy bone.	Compact bone thickness
	The total proportion, quantity, or volume in milk of all inorganic elements or compounds that have importance in body functions.	Milk total mineral amount
LPT	Any measurable or observable characteristic related to the proportion or amount in milk of the alpha fraction of the casein phosphoprotein.	Milk alpha-casein content
	Any measurable or observable characteristic related to the relative heaviness of the skeletal tissue of an animal following slaughter and removal of the head, digestive tract, internal organs, and possibly the hide and/or feet.	Dressed carcass bone weight
	Any measurable or observable characteristic related to the relative heaviness of the muscle tissue surrounding the femur of a bird.	Thigh muscle weight

Table 12: Three in-context examples used in the entity generation prompt for each ontology. Definitions are taken verbatim from the respective source ontology.